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Optimization of *Bauhinia monandra* seed oil extraction via artificial neural network and response surface methodology: A potential biofuel candidate

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ABSTRACT

The influence of sample weight, time, and solvent type and their reciprocal interactions on *Bauhinia monandra* seed oil (BMSO) yield using artificial neural network (ANN) and response surface methodology (RSM) was investigated. Also, the BMSO obtained was characterized to determine its aptness for oleochemical industry. Numerically predicted optimum values for the extraction process using RSM model were found to be the same for the developed ANN model. The optimum values were sample weight of 60 g, time of 100 min and petroleum ether with a corresponding BMSO yield of 14.8 wt%. Performance evaluation of the models by multiple coefficient of correlation (R), coefficient of determination (R^2) and absolute average deviation (AAD) showed that the ANN model was marginally better ($R = 0.9995$, $R^2 = 0.9991$, AAD = 0.27%) than the RSM model ($R = 0.9993$, $R^2 = 0.9986$, AAD = 0.49%) in predicting BMSO yield. Physicochemical properties of the BMSO such as acid value (7.56 mg KOH/g), indicated that it is non-edible and the fatty acids profile showed that the oil was highly unsaturated (87.9%), which makes it a potential candidate for biodiesel production.

1. Introduction

Energy utilization has increased immensely in the last century because of increased growth of World population, urbanization and industrialization. Though renewable energy is one of the World's fastest-growing energy sources, fossil fuels with their attendant problems, continue to supply almost 80 percent of World energy use through 2040 (EIA, 2013). Thus, there is the need for unconventional fuel that is renewable and can solve the problems of depletion of fossil fuels and their environmental concerns. These challenges have led to search for oils from plant sources to produce biodiesel. Such oils include sorrel oil, yellow oleander oil, neem oil, moringa oil, soybean oil, palm kernel oil, sesame oil, sunflower oil, rapeseed oil, karanja oil, jojoba oil and jatropha oil. The major problem associated with biodiesel as alternative fuel is its inherent higher price than the petro-diesel (Knothe et al., 2005). The higher price can be reduced using low-cost feedstock, which has ignited interest in materials such as waste oils, edible and non-edible oils. But there is growing debate on the use of edible oils for production of biodiesel. To deal with this concern, efforts should be directed towards identifying more plant oils that are non-food (such as *Bauhinia monandra*) and investigation on them should be focused on optimizing the extraction process involved.

B. monandra (kurz), also known as Napoleon's plume, is a species of leguminous trees, found in West Africa, Asia and West Indies, where it is use for ornamental purposes. In Brazil, the tree is conventionally used for treatments of diabetics and as a diuretic (Coelho and Silva, 2000; Pepato et al., 2002), and its leaf is a source of many antioxidant compounds (Argolo et al., 2004; Aderogba et al., 2006). The seed oil from *B. monandra* is highly unsaturated and the main fatty acids are oleic (11.5–18.1%), linoleic (50.4–60.8%), palmitic (15.1–23.1%) and stearic (6.4–9.4%) (Badami and Daulatabad, 1969; Balogun and Fetuga, 1985; Omode et al., 1995).

The need to optimize oil extraction process using solvent extraction cannot be overemphasized. It will save time, reduce production cost and maximize oil yield as well. But the conventional optimization method of one-factor-at-a-time is burdensome and time consuming. Also, it does not give chance to determine interactive effects of the factors under investigation. One of the ways employed currently in solving these problems is the application of response surface methodology (RSM) and artificial neural networks (ANN) to such processes. RSM is a statistical tool that describes the effect of the independent variables and their interactions in a process. It has been applied to various investigations on extraction of seed

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Nomenclature

AAD	Absolute average deviation
ANN	Artificial neural network
ANOVA	Analysis of variance
BMSO	*Bauhinia monandra* seed oil
IBP	Incremental back propagation
MFFF	Multilayer full feedforward
MNFF	Multilayer normal feedforward
QP	Quickprob
R	Multiple coefficient of correlation
R^2	Coefficient of determination
RSM	Response surface methodology
Tanh	Hyperbolic tangent function

oils from *Sesamuum indicum* (Betiku et al., 2012), *Hibiscus sabdariffa* (Betiku and Adepoju, 2013), *Piper nigrum* (Bagheri et al., 2014), *Nitraria tangutorum* (Liu et al., 2014) and biodiesel production from used vegetable cooking oil (Olutoye and Hameed, 2011). Whereas, ANNs are computational techniques developed based on neurons present in biological neural system such as the human system. Some of the benefits of ANNs are ability to handle incomplete data, noisy and very complex non-linear data and a capacity for parallel processing (Perpetuo et al., 2012). They can be used for predictions and data fitting once trained. ANNs have been applied to some studies with success (Rajendra et al., 2009; Perpetuo et al., 2012; Pouralinazar et al., 2012). But more recently, both RSM and ANN have been compared in investigations such as production of scleroglucan (Desai et al., 2008), production ethanol (Betiku and Taiwo, 2015), extraction of yellow oleander seed oil (Ajala and Betiku, 2014), yellow oleander biodiesel production (Betiku and Ajala, 2014), neem oil biodiesel production (Betiku et al., 2014), extraction of artemisinin from *Artemisia annua* (Pilkington et al., 2014). ANN is reported to be superior to RSM both in data fittings and prediction capabilities.

The focus of this work was on the modeling and optimization of seed oil extraction process of an underutilized and unconventional oilseed of *B. monandra*. The effect of extraction time, sample weight and solvent type and their reciprocal interactions on the oil yield were investigated. Additionally, the efficiencies of ANN and RSM as modeling and optimization tools were compared by determining the multiple coefficient of correlation (R), coefficient of determination (R^2) and absolute average deviation (AAD). The physical and chemical properties of the oil as well as its fatty acid profile were carried out in order to ascertain its suitability as an industrial feedstock.

2. Materials and methods

2.1. Materials

All reagents and chemicals used in this work were of analytical reagent (AR) grade obtained from BDH Chemicals Ltd., Poole England (petroleum ether and acetone), GFS Chemicals, Inc., 867 Mckinley Ave., Columbus OH (n-hexane).

2.2. Kernel sample preparation

Freshly matured fruits of *B. monandra* used were collected at the Obafemi Awolowo University, Ile-Ife Osun State, Nigeria located at latitude of 7.5183°N and longitude of 4.5228°E. The fruits were collected between August and September, 2013. The fleshy mesocarps/epicarps of gathered seeds were removed and sundried for two weeks, after which the fruits were shelled and decorticated.

Table 1
Factors and their levels for D-optimal design.

Type of factor	Variable	Unit	Symbol	Coded factor levels		
				−1	0	+1
Numeric						
	Sample weight	g	X_1	20	40	60
	Extraction time	min	X_2	20	60	100
Categorical						
	Solvent type	–	X_3	S_1	S_2	S_3

S_1 – n-hexane, S_2 – acetone, S_3 – petroleum ether.

These kernels were further sundried for five days until constant weight was achieved. The dried kernels were ground to powder using a plate mill machine.

2.3. BMSO extraction procedure

The method of Ajala and Betiku (2014) was employed for the extraction process. A 250-mL soxhlet apparatus and three different extraction solvents (n-hexane, acetone and petroleum ether) were evaluated. The apparatus was initially charged with a known weight of powdered *B. monandra* kernels, which was packed in a muslin cloth. A round bottom flask was filled with the extraction solvent (b.p. 50–70 °C) and the whole set up was heated up in a heating mantle for a known period of time. The extraction solvent in the solvent-oil mixture was recovered and recycled by distillation. The amount of BMSO extracted was determined gravimetrically as the ratio of the weight of BMSO extracted to the weight of powdered *B. monandra* kernels (Eq. (1)). The seed oil was stored appropriately for further analysis.

$$\text{BMSO yield }(\%) = \frac{\text{weight in gram of seed oil extracted}}{\text{weight in gram of kernels powder}} \times 100 \qquad (1)$$

2.4. Experimental design

D-optimal design method was applied in designing experiments used in this work. The D-optimal method gives smaller number of experiments with respect to other design methods and can handle categorical factors included in the design of experiment (Kuram et al., 2013). The experimental design employed in this present work has two numerical factors (sample weight (g), extraction time (h)) and a categorical factor (solvent type) designated as X_1–X_3, respectively. The minimum, center point and maximum levels of each variable were coded as −1, 0, and +1, respectively (Table 1). A three-level-three-factor design was applied, which produced 24 experimental runs, which comprises of 14 full factorial points, 7 axial points, 2 center-axial points and 1 center full-factorial.

Table 2 shows the run order, experimental design and the observed response (BMSO yield) for the three variables and 24 experimental runs generated. These were carried out in two replicates and the average values are presented. A quadratic polynomial, including all interaction terms, was used to calculate the response:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_{12} X_1 X_2 + \beta_{13} X_1 X_3 + \beta_{23} X_2 X_3 + \beta_{11} X_1^2 + \beta_{22} X_2^2 + \beta_{33} X_3^2 \qquad (2)$$

where Y is the predicted response variable (BMSO yield), β_0 is the intercept term, β_1–β_3 are the linear coefficients, β_{12}, β_{13}, and β_{23} are the interaction coefficients, β_{11}, β_{22}, and β_{33} are the quadratic coefficients, and X_1–X_3 are the coded independent variables.

2.5. RSM statistical analysis

The experimental data obtained were subjected to multiple regression analysis using the Design Expert software package ver-

Table 2
D-optimal design, actual and predicted values for three-level-three-factor response surface analysis.

Run	Numerical factors		Categorical factor	Actual oil yield (wt%)	RSM predicted oil yield (wt%)	ANN predicted oil yield (wt%)
	X_1	X_2	X_3			
1	**20**	**20**	$\boldsymbol{S_1}$	**8.56**	**8.47**	**8.56**
2	60	60	S_3	14.73	14.73	14.71
3	60	60	S_1	13.50	13.51	13.50
4	40	20	S_2	13.18	13.14	13.14
5	20	100	S_2	9.48	9.67	9.69
6	60	20	S_3	14.48	14.45	14.49
7	20	100	S_1	8.85	8.92	8.89
8	**40**	**20**	$\boldsymbol{S_2}$	**13.10**	**13.14**	**13.14**
9	20	100	S_1	8.93	8.92	8.89
10	60	100	S_2	14.49	14.53	14.50
11	60	100	S_3	14.80	14.82	14.81
12	60	20	S_1	12.96	12.97	12.96
13	60	100	S_1	13.88	13.85	13.88
14	40	60	S_2	13.22	13.11	13.22
15	**40**	**60**	$\boldsymbol{S_1}$	**11.92**	**11.93**	**11.92**
16	20	20	S_3	10.45	10.49	10.45
17	20	60	S_3	10.58	10.55	10.58
18	20	60	S_2	9.90	10.00	9.90
19	40	60	S_3	13.40	13.42	13.40
20	60	100	S_1	13.88	13.85	13.88
21	60	100	S_2	14.51	14.53	14.50
22	**20**	**100**	$\boldsymbol{S_3}$	**10.45**	**10.43**	**10.45**
23	20	100	S_2	9.90	9.67	9.69
24	40	20	S_1	11.43	11.50	11.43

X_1 – sample weight, X_2 – extraction time, X_3 – solvent type, S_1 – *n*-hexane, S_2 – acetone, S_3 – petroleum ether, bold rows represent testing data set and normal rows represent training data set.

sion 9.0.2 (Stat-Ease Inc., Minneapolis, MN, USA) to obtain the coefficients of the quadratic equation. The multiple correlation coefficient (R) and coefficient of determination (R^2) were calculated to evaluate the performance of the regression equation. The performance of the model in the experimental area was investigated graphically. Statistical evaluation of the RSM model was carried out using analysis of variance (ANOVA), which is required to test the significance of the model.

2.6. Modeling by artificial neural network (ANN)

NeuralPower, version 2.5 (CPC-X Software) was used throughout this work. Multilayer normal feedforward and multilayer full feedforward neural networks were used to predict the BMSO yield. Networks were trained by different learning algorithms (incremental back propagation – IBP, batch back propagation – BBP, quickprob – QP, and genetic algorithm – GA). The ANN architecture included an input layer with three neurons, an output layer with one neuron, and a hidden layer. In order to determine the optimal network topology, only one hidden layer was used and the number of hidden and output layers (sigmoid, hyperbolic tangent (Tanh), Gaussian, linear, threshold linear and bipolar linear) were iteratively determined by developing several networks (Ajala and Betiku, 2014; Betiku and Taiwo, 2015). A total of 20 of the experimental data were used to train the network and the remaining data was used for testing (Table 2).

2.7. Verification of estimated data

Evaluation of the developed ANN and RSM models estimation capabilities were determined. For this purpose, the models output error between the experimental and predicted values were estimated. The R, R^2, and AAD were determined and their values were used to together to juxtapose RSM and ANN models by comparing the evaluated values for the models. The accuracies of the models were determined by assessing R, R^2 and AAD values. R shows the relationship between the predicted and experimental values while R^2 describes the degree of fit for the mathematical model. AAD defines the level of accuracy of a model prediction.

AAD is defined in Eq. (3) as:

$$\text{AAD}\ (\%) = \left(\frac{1}{n} \sum_{i=1}^{n} \left(\frac{y_{\text{pred}} - y_{\text{exp}}}{y_{\text{exp}}} \right) \right) \times 100 \quad (3)$$

where y_{pred} and y_{exp} are the predicted and experimental responses, respectively, and n is the number of the experimental data. The model with lowest AAD, highest R^2 and R is considered best (Ajala and Betiku, 2014; Betiku and Taiwo, 2015).

2.8. Physicochemical properties and fatty acid composition of BMSO

BMSO properties such as moisture content, acid value, % free fatty acid (FFA), kinematic viscosity, specific gravity, iodine value, saponification value and peroxide value were determined by the methods of Association of Official Analytical Chemists (AOAC, 1995). ATAGO digital Refractometer (Model RX – 5000α, Atago Co., Ltd., Japan) was used for refractive index measurement. Water at 25 °C was circulated round the glass slide to keep its temperature uniform in the refractometer. Then, few drops of BMSO sample were dropped on the glass slide of the refractometer by means of syringe and needle. The refractive index was read from the digital display. This was repeated twice and the average value was taken (Ajala and Betiku, 2014). All the parameters were determined in duplicates and the average values were reported. The method of Betiku and Adepoju (2013) was used for determining fatty acid composition of the BMSO.

3. Results and discussion

3.1. Modeling and variables optimization by RSM

Table 2 shows the D-optimal design and results of the 24 experiments carried out. The regression models in terms of the actual factors that described the extraction process are presented in Eqs.

Table 3
Test of significance for every regression coefficient and ANOVA.

Source	SS	df	MS	F-value	p-value
Model	103.32	11	9.39	792.86	<0.0001
X_1	94.32	1	94.32	7961.45	<0.0001
X_2	0.28	1	0.28	23.30	0.0004
X_3	9.06	2	4.53	382.24	<0.0001
X_1X_2	0.12	1	0.12	9.86	0.0085
X_1X_3	0.25	2	0.12	10.38	0.0024
X_2X_3	0.61	2	0.3	25.56	<0.0001
$X_1{}^2$	1.41	1	1.41	119.35	<0.0001
$X_2{}^2$	0.04	1	0.04	3.02	0.1076
ANOVA					
Model	103.32	11	9.39	792.86	<0.0001
Residual	0.14	12	0.012		
Lack of Fit	0.047	7	0.0068	0.36	0.8941
Pure Error	0.095	5	0.019		
Total SS	103.46	23			

$R = 0.9993$, $R^2 = 0.9986$ and adjusted $R^2 = 0.9974$

X_1 – sample weight, X_2 – extraction time, X_3 – solvent type, SS – sum of squares, MS – mean square.

(4)–(6). The results of test of significance for every regression coefficient and ANOVA are presented in Table 3. The goodness of fit of the regression model was assessed by R and R^2. The value of R (0.9993) of the model shows an excellent agreement between the predicted and observed values. The model R^2 of 0.9986 suggests that the sample variation of 99.86% for BMSO extraction is ascribed to the independent variables and only 0.14% of the total variation are not described by the model (Ajala and Betiku, 2014; Betiku and Taiwo, 2015). The adjusted R^2 (0.9974) was sufficiently high to indicate the significance of the model. It has been suggested that R^2 should be at least 80% for a good fit of a model (Joglekar and May, 1987). The model F-value of 792.86 and $p < 0.0001$ imply that the model is significant. The "lack of fit F-value" of 0.36 implies the lack of fit is not significant relative to the pure error, which is desirable (Table 3). Also, all the model terms are significant at 95% confidence level except the quadratic form of the solvent type ($X_3{}^2$).

Solvent type S_1 (n-hexane):

$$Y = 3.69 + 0.27X_1 + 0.01X_2 + 0.0001X_2 - 0.002X_1^2 - 0.00006X_2^2 \quad (4)$$

Solvent type S_2 (acetone):

$$Y = 5.64 + 0.26X_1 - 0.0016X_2 + 0.0001X_1X_2 - 0.0012X_1^2 - 0.00006X_2^2 \quad (5)$$

Solvent type S_3 (petroleum ether):

$$Y = 6.10 + 0.25X_1 + 0.004X_2 + 0.0001X_1X_2 - 0.002X_1^2 - 0.00006X_2^2 \quad (6)$$

where Y is the BMSO yield (wt%), X_1 is the sample weight (g), X_2 is the extraction time (h), X_3 is the solvent type.

The optimal condition values of the independent variables selected for the extraction process were found by applying regression analysis to Eq. (6) using the Design Expert software package version 9.0.2 (Stat-Ease Inc., Minneapolis, MN, USA). The optimum values were statistically predicted as sample weight of 60 g, extraction time of 100 min and solvent type of petroleum ether with a corresponding BMSO yield of 14.8 wt%. The model was validated by applying the optimum values to three independent experimental replicates and the average value of BMSO yield obtained was 14.8 wt%. This is a confirmation of the effectiveness of the RSM model in describing the extraction process.

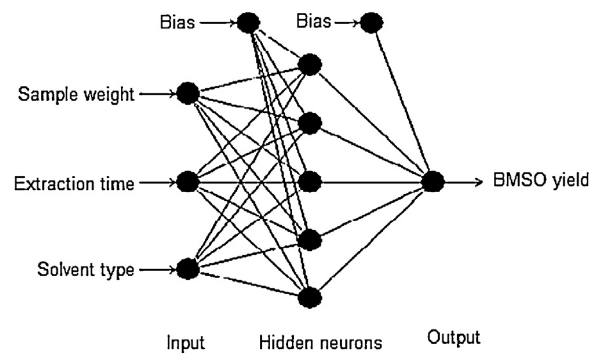

Fig. 1. ANN architecture for BMSO extraction.

3.2. ANN modeling and variables optimization

ANNs were applied to model the extraction of seed oil from *B. monandra* oilseed. A number of neural network architectures and topologies of ANN were selected and investigated for estimation and prediction of BMSO yield. This is due to the fact that the choice of an optimal neural network architecture and topology is critical for successful application of ANN.

Likewise, the learning algorithm types described in the literature are many and it is difficult to know ahead which of the learning algorithms will be more effective for a given problem (Saracoglu, 2008). Furthermore, the transfer function types used influence the neural network learning rate and aid its performance (Baş and Boyaci, 2007). The results obtained in this work showed that quick-prob (QP) was the most successful algorithm for BMSO extraction process (Table 4). To determine the optimum number of neurons in the hidden layer, a series of network topologies was studied by varying the number of neurons from 1 to 8. The networks estimation capability and predictability were measured by R, R^2 and AAD. The best topology (3–5-1), which has three inputs, five neurons as the optimum and one output, was chosen. MNFF connection type and QP network with Tanh as hidden and Tanh as output layer functions was the best ANN model for the extraction process (Fig. 1). The values of R, R^2, and AAD for training data set were 0.9995, 0.9989, and 0.30%, respectively, while for testing data set, the values were 1.0000, 0.9998 and 0.08%, respectively. Then for the whole data set, $R = 0.9995$, $R^2 = 0.9991$, and AAD = 0.27%. R^2 greater than 0.80 confirmed the good fit of the model developed (Joglekar and May, 1987).

The ANN model coupled with generic algorithm was used to generate the optimal condition values for the extraction process. These were sample weight of 60 g, extraction time of 100 min and petroleum ether as solvent type with a corresponding 14.8 wt%. The model was validated by applying these optimal condition values to two independent experimental replicates and the average oil yield obtained was 14.8 wt%, which was within the range predicted. The validation results demonstrated efficiency of the model in adequately describing the extraction process.

The importance level of process variables on the BMSO extraction was investigated using NeuralPower, version 2.5 (CPC-X Software). The results showed sample weight with 46% was the most important variable followed by extraction time with 39% and solvent type with 15% (Fig. 2).

Table 4
The effects of different neural network architecture and topologies on R^2 and AAD.

Topology	Learning algorithm	Connection type	Output layer transfer function	Hidden layer transfer function	R^2 for whole data	AAD for whole data (%)	R^2 for training set	AAD for training set (%)	R^2 for testing set	AAD for testing set (%)
3–5-1	QP[a]	MNFF[b]	Tanh[c]	Tanh	0.9991	0.27	0.9989	0.30	0.9998	0.0798
3–5-1	QP	MFFF[d]	Tanh	Tanh	0.9991	0.28	0.9988	0.32	0.9998	0.0818
3–4-1	QP	MFFF	Tanh	Tanh	0.9989	0.35	0.9987	0.40	0.9998	0.1200
3–3-1	QP	MNFF	Tanh	Tanh	0.9985	0.52	0.9986	0.25	0.9975	0.7187
3–5-1	GA[e]	MFFF	Tanh	Tanh	0.9631	2.56	0.9557	3.07	1.0000	0.000

[a] Quickprob.
[b] Multilayer normal feedforward.
[c] Hyperbolic tangent function.
[d] Multilayer full feedforward.
[e] Genetic algorithm.

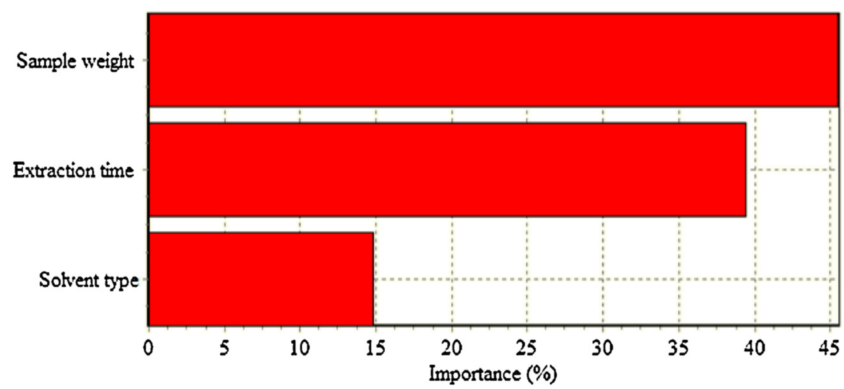

Fig. 2. Level of importance of process variables on BMSO yield.

3.3. Relationship among the selected variables

The interactions among the process variables were investigated by plotting three dimensional response surfaces using NeuralPower, version 2.5 (CPC-X Software). The effect of extraction time and sample weight using *n*-hexane as the extraction solvent, is displayed in Fig. 3a. The extraction time and the sample weight are directly related to BMSO yield. As the time and sample weight increase, BMSO yield increases. Fig. 3b depicts the effects of the sample weight and the extraction time on BMSO yield with acetone as the extraction solvent. While the interaction between sample weight and extraction time using petroleum ether as extraction solvent is presented in Fig. 3c. The trend in both cases followed that of Fig. 3a. As the time and sample weight increase, BMSO yield also increases. But petroleum ether as extraction solvent had the highest positive effect on BMSO yield followed by acetone. Ajala and Betiku (2014) reported that petroleum ether as extraction solvent is better than *n*-hexane in the work carried out on yellow oleander seed oil extraction. This may be because the boiling point and the polarity index of petroleum ether are lower than that of *n*-hexane (Yang et al., 2014), causing the molecules of petroleum ether to travel faster through the powdered seed than that of *n*-hexane during the extraction process, thus leading to higher BMSO yield.

3.4. Performance assessment of ANN and RSM models

The accuracies of the ANN and RSM models in describing the oil extraction process were determined by evaluating R, R^2 and AAD. The results demonstrated that both RSM and ANN models displayed good predictions based on the values of R, R^2 and AAD (Table 5). The values of R^2 for RSM and ANN were 0.9986 and 0.9991, respectively, while the values of AAD for RSM and ANN were 0.49 and 0.27%, respectively. But ANN showed a slight edge over RSM due to higher value of R^2 and smaller value of AAD (Table 5). In addition, data fitting of the models were investigated and both models demonstrated good fittings (Fig. 4).

Table 5
Appraisal of ANN and RSM models.

Variable	ANN	RSM
Sample weight (g)	60	60
Extraction time (min)	100	100
Solvent type	petroleum ether	petroleum ether
R	0.9995	0.9993
R^2	0.9991	0.9986
AAD (%)	0.27	0.49

Table 6
Physicochemical characteristics of BMSO.

Parameter	Mean value
Physical properties	
Physical state at 25 °C	Liquid/Light green in colour
Moisture content (%)	0.025
Refractive index	1.467
Specific gravity	1.023
Kinematic Viscosity (mm^2/s) at 40 °C	43.51
Chemical properties	
%FFA (as oleic acid)	3.78
Acid value (mg KOH/g)	7.56
Saponification value (mg KOH/g)	197.22
Iodine value (g I_2/100 g oil)	56.30
Peroxide value (meq O_2/kg oil)	1.98
Higher heating value (MJ/kg)	44.16
Other property	
Cetane number	61.31

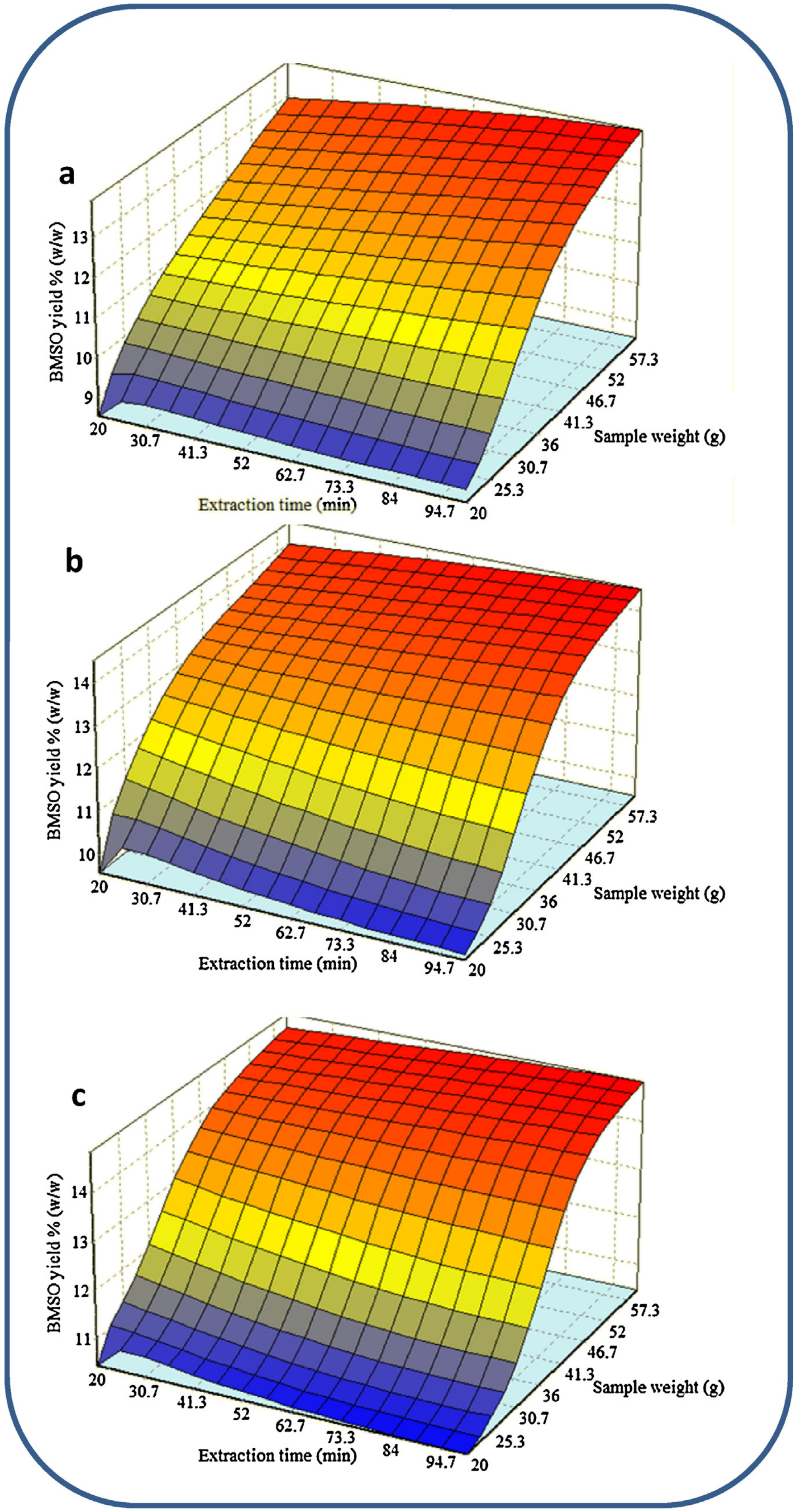

Fig. 3. Response surface plots for BMSO extraction with (a) *n*-hexane, (b) acetone, and (c) petroleum ether as extraction solvents.

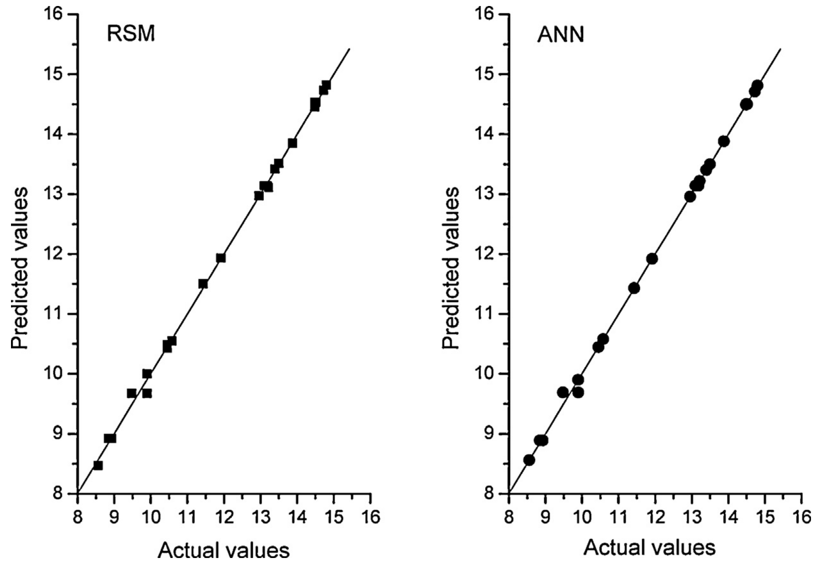

Fig. 4. Plots for predicted values against experimental values for BMSO extraction process.

Table 7
Fatty acid composition of the BMSO.

Fatty acid	Structure	% Composition	Badami and Daulatabad (1969)	Omode et al. (1995)	Balogun and Fetuga (1985)
Saturated fatty acid					
Myristic	C14:0	0.4	1.4	ND	1.4
Palmitic	C16:0	8.8	15.1	18.9	23.1
Stearic	C18:0	2.2	9.4	9.0	6.4
Arachidic	C20:0	0.4	0.9	ND	0.4
Behenic	C22:0	0.3	0.9	ND	ND
Total		12.1	27.7	27.9	31.4
Unsaturated fatty acid					
Palmitoleic	C16:1	0.5	ND	ND	0.1
Oleic	C18:1	25.6	11.5	16.5	18.1
Linoleic	C18:2	61.2	60.8	55.0	50.4
Linolenic	C18:3	0.6	ND	ND	0.2
Total		87.9	72.3	71.5	68.6

ND: Not detected.

3.5. Physicochemical properties of BMSO

The quality of the BMSO was assessed by determining its physical and chemical properties (Table 6). The oil had a moisture content of 0.025%. The specific gravity and kinematic viscosity of the oil were 1.023 and 43.51 mm^2/s, respectively. The kinematic viscosity value reported by Omode et al. (1995) for BMSO was 10.9 mm^2/s, which is quite lower than the observed value in this work. This may be explained by higher specific gravity of the oil obtained in this work compared with 0.914 reported by Omode et al. (1995). The acid value and %FFA of BMSO in this present work were 7.56 mg KOH/g oil and 3.78, respectively. These values are within the range reported in literature (Omode et al., 1995; Anhwange et al., 2005). Saponification and peroxide values of the BMSO were 197.22 mg KOH/g oil and 1.98 meq O_2/kg oil, respectively, and they are in close proximity to values earlier reported (Badami and Daulatabad, 1969; Omode et al., 1995; Anhwange et al., 2005). The saponification value suggests that the main fatty acids present in the BMSO were of high molecular mass. High peroxide value is associated with high rate of rancidity and the value varies with the degree of unsaturation. The rate of oxidation of fat and oil also increases with increasing level of unsaturation (Ikyenge et al., 2012). Peroxide value obtained suggests that the oil was less susceptible to rancidity at room temperature. Iodine value indicates the level of unsaturation of an oil or a fat (Knothe, 2002). The iodine value of BMSO (56.30 g I_2/100 g oil) shows a high level of unsaturation. Badami and Daulatabad (1969) reported iodine value of BMSO that is double the value observed in this present work. The European standard that describes the requirements and test methods (EN 14214) suggested maximum iodine value of 120 g I_2/100 g oil for biodiesel. The value obtained for BMSO indicated it is a good feedstock for biodiesel production. Cetane number gives an indication of combustion efficiency of a fuel inside a compression engine. The cetane number of BMSO observed in this work satisfied the limits suggested by ASTM (2003) D 6751 and EN (2008) 14214 for biodiesel, making it a possible biodiesel feedstock.

The fatty acids present in the BMSO are shown in Table 7. These results showed that the oil was highly unsaturated (87.9%) with the main fatty acids as oleic (25.6%), linoleic (61.2%), palmitic (8.8%) and stearic (2.2%). These observations are corroborated by values reported in the literature (Badami and Daulatabad, 1969; Balogun and Fetuga, 1985; Omode et al., 1995). But the palmitic and stearic levels observed in this work were lower than the values earlier reported (Table 7). It is recommended that the linolenic acid and polyunsaturated methyl ester ($\geq$4 double bonds) contents in biodiesel should not be greater than 12 and 1%, respectively (EN 14,214). This confirmed that BMSO with 0.6% linolenic acid content and no presence of polyunsaturated fatty acid with $\geq$ 4 double bonds should be a good candidate for biodiesel production. Also, the high unsaturated fatty acid content of BMSO makes its methyl esters suitable properties with respect to biodiesel specifications (ASTM D 6751 and EN 14214).

4. Conclusions

D-Optimal design of RSM with a categorical factor such as solvent type was successfully applied to the optimization of BMSO extraction process. Petroleum ether was found to be the best among the three solvents investigated. The best RSM model that describes the BMSO extraction process was a significant (p<0.05) quadratic polynomial. On the order hand, the best ANN model for the extraction process was achieved by quickprob algorithm with Tanh as both the output and hidden transfer functions. The predicted optimum levels were the same for both models: sample weight of 60 g, extraction time of 100 min and petroleum ether as the solvent type with BMSO yield (14.8 wt%). The results of the evaluation of the efficiency of the optimization tools showed that ANN was slightly better than RSM both in predictions and data fitting. The physicochemical properties of the BMSO indicated that it may be a good feedstock for biodiesel production.

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